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The entrepreneur's experiential diversity and entrepreneurial performance

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Abstract This study examines the relationship between the entrepreneur's experiential diversity and entrepreneurial performance. First, we argue that entrepreneurial and industry experiences are positively associated with performance. Second, by combining Lazear's jacks-of-all-trades theory with the cognition and learning literatures, an inverted U-shaped experience diversity-performance relationship is predicted. The hypotheses are tested using data from the US National Labor Survey Youth 1979 and O*NET. We find that industry experience is positively associated with performance, but entrepreneurial experience is negatively related. Moreover, experience diversity measured in terms of skills is found to be positively associated with performance up to a certain threshold. After this threshold, an increase in an entrepreneur's experiential diversity lowers performance. Entrepreneurs with 23 different skills have the highest performance. Furthermore, when depreciating for experience, experience diversity measured in terms of both skills and knowledge is found to be positively related to performance.

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1 Introduction

Over the past decade, much work has been done attempting to identify the reasons as to why some individuals become an entrepreneur and why some of these individuals are better in being an entrepreneur than others (Noorderhaven et al. 2004; Verheul et al. 2002). Several studies relate to the economy as a whole, focusing on factors that push and pull an individual into entrepreneurship (Parker 2004). Other research examines the effect of an individual's experience with colleagues and parents being entrepreneurs (Nanda and Sørensen 2010). Lazear's (2005) jacks-of-all-trades theory identifies another reason for an individual to make the switch to entrepreneurship. In this theory, the central argument is that the more diverse experience gained in paid employment, the more likely this individual is to become an entrepreneur. Since an entrepreneur needs to perform many different tasks, she needs to have diverse knowledge and skills. Much of this required knowledge and skills develops from experience. Furthermore, the jacks-of-all-trades theory claims that an entrepreneur's performance is determined by her weakest skill (Lazear 2005: 655). Empirical evidence has been reported by Åstebro and Thompson (2011), Åstebro and Yong

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(2016), Bublitz and Noseleit (2014), and Hartog et al. (2010).

The contribution of the current paper is twofold. First, our study adds to the literature by examining the boundary conditions of the jacks-of-all-trades theory. In order to do so, this paper combines the learning literature and the literature on human cognition with that regarding the jacks-of-all-trades theory. Jacks-of-all-trades studies have focused on the effect of an entrepreneur's balanced skill set on the probability of becoming an entrepreneur, as well as her success as an entrepreneur. However, according to cognition and learning literatures, an entrepreneur is constrained in the number of skills she can develop and maintain well, due to her cognitive limitations (Baron 1998; Gilbert et al. 1992). This negative effect to experience diversity on performance is found by Åstebro and Thompson (2011) and Åstebro and Yong (2016), studying whether experiential diversity has a negative or a positive effect. However, the positive findings of experiential diversity on performance reported by Bublitz and Noseleit (2014) and Hartog et al. (2010) and the negative findings of experiential diversity found by Åstebro and Thompson (2011) suggest an optimal degree of experiential diversity. Hence, instead of studying the effect of a balanced skill set on entrepreneurial performance, this study is the first to examine a non-linear relationship between skill diversity and entrepreneurial performance. That is, what degree of diversity of a skill set is associated with the highest entrepreneurial performance?

Second, by combining a 1979–2010 US dataset, capturing the individuals' career from the start of their working life, with the O*NET occupational classification, we can determine an individual's skills and knowledge sets and follow their development over time. This study's dataset comprises the skill types and knowledge domains in which an individual has cumulated experience, and when this was the case. Extant jacks-of-all-trades work studying the effect of experience diversity on entrepreneurial performance either uses skills possessed before the start of the entrepreneur's career (Hartog et al. 2010), or the number of different occupational fields and industries an entrepreneur has experience in (Åstebro and Yong 2016; Åstebro et al. 2011). The former neglects the knowledge and skills learned during an individual's working life, whereas the latter ignores the possible synergies between different occupational fields and industries. We add to this by creating time-varying measures in which we unpack the number of occupations into the skill and knowledge sets gained in these occupations. We estimate the optimal number of skills and knowledge domains associated with the highest entrepreneurial performance. By doing so, we further open the black box of experience.

This paper adopts Lechmann and Schnabel's (2014) focus on the self-employed as solitude entrepreneurs. The self-employed provide an ideal context to test the jacks-of-all-trades theory, because such solo-entrepreneurs are not able to delegate any activities and tasks to employees, having none. Although self-employed have the possibility to outsource activities and tasks, this effect is limited because essential activities and tasks for entrepreneurs, such as opportunity seeking and opportunity seizing (Shane and Venkataraman 2000; Sternberg and Wennekers 2005), cannot be outsourced easily, or not at all.

2 Theoretical background and hypotheses

2.1 Learning from experience

The strand of literature concerned with entrepreneurial learning tries to answer three questions (Cope 2005; Parker 2006). The first question is about what entrepreneurs learn. According to Minniti and Bygrave (2001), knowledge is cumulative. Hence, knowledge acquired in the present builds upon knowledge learned in the past. Entrepreneurs rely heavily on their knowledge gained from previous experiences when making strategic decisions (Fern et al. 2012). They need to possess two types of knowledge to be able to make entrepreneurial decisions efficiently and effectively (Minniti and Bygrave 2001). The first type is about the market and market opportunities, and the second type refers to the entrepreneurial skills and abilities an entrepreneur needs to be able to run a business. This view is shared by Unger et al. (2011), arguing that knowledge relating to managerial and industry experience is more important to perform entrepreneurial tasks efficiently and effectively than is more general knowledge. Industry and managerial experience have slightly different effects on the choices an entrepreneur makes (Dencker and Gruber 2015). Entrepreneurs with industry experience are more likely to stick with what they know, and thus stay in the same industry as before they became entrepreneur. Managerial experience broadens the scope of potential opportunities entrepreneurs can exploit. Managerial experience may give an entrepreneur greater benefits than industry experience, as the former operates less as a constraint on an entrepreneur's decision making (Dencker and Gruber 2015).

Literature on learning finds that knowledge and skills are both outcomes from experience, in which knowledge relates to the "relatively formal and established facts, rules, policies and procedures" (Nass 1994: 39) and skills refer to "information-processing abilities gained from learning by doing and the ability to generate new procedures and conclusions" (Nass 1994: 40). Yet, there remains some discussion on what the outcome of experience is (Levitt and March 1988; Minniti and Bygrave 2001; Nass 1994; Unger et al. 2011). Some scholars have mainly emphasized skills as the outcome of experience (see, for example, Levitt and March 1988), while others primarily focus on knowledge as the outcome of experience (see, e.g., Minniti and Bygrave 2001; Nass 1994).

The second question involves how entrepreneurs learn. The argument made by several scholars is that entrepreneurs learn primarily through learning-by-doing (Cope and Watts 2000; Minniti and Bygrave 2001). Learning-by-doing includes several learning processes, of which the most important one is repetitious processes of trial and error (Nicholls-Nixon et al. 2000). Both Dalley and Hamilton (2000) and Minniti and Bygrave (2001) develop the argument that the only way in which an entrepreneur can learn is through learning-by-doing. Hence, entrepreneurs can only acquire their knowledge from experience with their own past actions. Dalley and Hamilton (2000: 55) even go as far as to argue that "there can never be any substitute for experience." Other learning processes put forward in the literature concern problem solving and discovery (Young and Sexton 1997). Gibb (1997) distinguishes between seven modes of learning: learning from peers, learning-by-doing, learning from feedback from customers and suppliers, learning-by-copying, learning-by-experimenting, learning-by-problem solving and opportunity taking, and learning from mistakes.

Within the context of experiential learning, the literature differentiates between the degrees to which an event offers the opportunity to learn. So-called critical events trigger higher-level learning (Appelbaum and Goransson 1997; Cope 2005). These critical events include crises, failures, or mistakes. A key characteristic of these critical events is that they force the entrepreneur to change routines and standardized responses, as the event is non-standard and developed routines no longer prove to be valid and effective (Appelbaum and Goransson 1997). The central argument is that entrepreneurs learn more from critical events than from non-critical experiences, because these non-critical experiences do not force the entrepreneur to rethink routines and standardized approaches. Therefore, these non-critical experiences are argued to stimulate lower-level learning only (Cope 2005).

Other terms used in the literature for the different levels of learning are zero learning, single-loop learning, double-loop learning, and triple-loop learning (Argyris and Schön 1978; Argyris 1996; Romme and van Witteloostuijn 1999). Zero learning is the lowest level of learning. Though problems arise, no corrective actions are taken. Single-loop learning involves changes of the entrepreneur's knowledge, but does not trigger the adaptation of policies and/or objectives. This level of learning relates to the question: "are we doing things right?" With double-loop learning, the detected mistakes require corrective actions that change the policies and objectives of an entrepreneur. This level of learning involves the question: "are we doing the right things?" Triple-loop learning is the highest level of learning, in which learning and detected mistakes lead an entrepreneur to change learning strategies and develop new learning processes (Romme and van Witteloostuijn 1999).

Although an entrepreneur may learn the most from failure, failure to succeed sends out negative signals to an entrepreneur's environment, which reduces the likelihood that she will receive funding to start a new business in the future (Gompers et al. 2010; Hsu 2007). Hsu (2007) hypothesizes that entrepreneurs who have failed might have more difficulty in obtaining funding, because of the negative signal that prior failure gives to the potential funders. Entrepreneurs with prior success, in contrast, have more success in obtaining funding. Furthermore, they have a larger network of (potential) funders. Gompers et al. (2010) find similar results, showing that entrepreneurs with a track record of successes have an increased likelihood to receive the needed resources vis-à-vis entrepreneurs who have failed in the past.

The third question is why entrepreneurs learn. Baum et al. (2011) show that entrepreneurial learning will increase entrepreneurial performance. Cressy (1992) argues that this relationship between entrepreneurial learning and increased performance is a result of an increased understanding of the causal effects running from certain actions to specific outcomes. Parker (2006) reveals that when entrepreneurs have to decide on a future project, they value knowledge from past experience from failures and successes more highly than knowledge gained from signals and information revealed through the market and the environment.

By providing answers to these three questions, the literature on entrepreneurial learning identifies a three-step mechanism. The question as to how entrepreneurs learn relates to the causal relationship between experience and learning (Cope 2005; Minniti and Bygrave 2001). Subsequently, entrepreneurs are assumed and theorized to develop knowledge and capabilities through learning (Rae and Carswell 2000). Hence, this reflects the causal relationship between learning and capabilities. The question of why entrepreneurs learn reflects the causal relationship between capabilities and performance. Indeed, Baum et al. (2011) have shown that learning results in higher entrepreneurial performance.

Hypothesis 1 (H1): The entrepreneur's experience is positively related to entrepreneurial performance.

2.2 Experience diversity

According to Lazear's theory of jacks-of-all-trades, entrepreneurs should have a basic level of knowledge regarding many different business areas (Lazear 2004, 2005). The reason for this is that an entrepreneur performs many different tasks. Thus, the entrepreneur needs many different capabilities to be able to perform all these different tasks, implying that she must have widespread experience across different business areas. Specifically, Lazear (2005) argues that the higher the experience diversity gained before becoming an entrepreneur, the larger the number of capabilities that the to-be-entrepreneur possesses and, thus, the more likely this individual is to become an entrepreneur. Furthermore, he highlights the difference between being a salary worker and being an entrepreneur. An individual in paid employment receives the income associated with her best skill. However, if this individual were to be an entrepreneur, she will be limited by her weakest skill. Therefore, an entrepreneur's weakest skill determines her success.

Following this line of reasoning, Lazear (2005) argues that there is no use for entrepreneurs to develop expert skills in one area, while having only basic skills in another area. The reason for this is that, according to the jacks-of-all-trades theory, the weakest skill determines the success of an entrepreneur. Hence, an entrepreneur should be relatively good, or relatively bad, in all required skills. When these required skills are correlated, obtaining a high level on all of these required skills is easier (Lazear 2005). However, when these skills are not correlated, it becomes much more difficult, if not impossible, to obtain a high level on all of these required skills. This lowers the entrepreneur's chances of turning successful, given that the weakest skill determines the entrepreneur's success (Lazear 2005).

Lechmann and Schnabel (2014) find empirical support for Lazear's (2005) jacks-of-all-trades theory for a sample of self-employed. Their findings show that entrepreneurs do indeed perform many different tasks, with entrepreneurs performing more tasks than individuals in paid employment. In contrast to Lazear's (2005) argument, Lechmann and Schnabel (2014) reveal that just possessing a basic level of each required skill is insufficient. An individual should have expert skills on all of these different areas, rather than a just basic understanding. Lechmann and Schnabel (2014) explain this finding by arguing that self-employed cannot delegate tasks to the employees, having none. So, these self-employed have to perform these tasks themselves. To be able to do so, they need expert skills. Although it could be argued that self-employed have the possibility to outsource activities and tasks, the options to do so are limited. Vital activities for entrepreneurs, such as opportunity-seeking and opportunity-seizing (Shane and Venkataraman 2000; Sternberg and Wennekers 2005), cannot be outsourced.

In contrast to Lechmann and Schnabel (2014), Hartog et al. (2010) find mixed support for Lazear's jacks-of-all-trades theory. Instead of measuring the effect of experience diversity on the likelihood of becoming an entrepreneur and entrepreneurial performance, Hartog et al. (2010) measure the effect of skill diversity at the start of someone's working life on the likelihood of becoming an entrepreneur and entrepreneurial performance. In their study, five types of skills are included—i.e., verbal, mathematical, technical, clerical, and social skills. The results show that skill diversity does not influence the likelihood to become an entrepreneur. However, skill diversity does affect entrepreneurial performance. Entrepreneurs with a larger number of the different skills have higher income. Skill diversity does not influence the earnings of an individual in paid employment.

Contrary to Hartog et al. (2010) and in line with Lechmann and Schnabel (2014) and Lazear (2005), Åstebro and Thompson (2011) find evidence of individuals with more diverse experience to be more likely to become an entrepreneur. However, they find mixed support for the effect of having diverse experience on entrepreneurial performance. Whereas Åstebro and Thompson (2011) report negative effects, Åstebro and Yong (2016) find mixed results. In the latter study, experience diversity measured as the number of occupational fields has a positive effect on entrepreneurial performance, but experience diversity measured as the number of industries has a negative impact on the entrepreneur's performance.

The argument made by Lazear (2005) and the evidence reported by Hartog et al. (2010), Lechmann and Schnabel (2014), and Åstebro and Yong (2016) are in line with the literature on entrepreneurial learning. Just like Lazear (2005), Minniti and Bygrave (2001), and Unger et al. (2011) argue that an entrepreneur should have knowledge regarding different areas of expertise (i.e., general knowledge, managerial knowledge, and industry knowledge) to be able to run a profitable business. And just like Lazear (2005), Minniti and Bygrave (2001), and Unger et al. (2011) reason that the knowledge an entrepreneur should possess is to be gained and learned through experience, which implies that the entrepreneur must have diverse experience to develop the required knowledge across different areas of expertise.

Hence, on the one hand, we may have a positive relationship between experience diversity and entrepreneurial performance, stemming from the learning opportunities associated with each new experience. With each new experience, the entrepreneur gains new knowledge and skills through learning-by-doing. This results in newly developed entrepreneurial capabilities, which will ultimately result in higher entrepreneurial performance. On the other hand, we may have a negative relationship between experience diversity and entrepreneurial performance, as was found by Åstebro and Thompson (2011) and Åstebro and Yong (2016), for different reasons.

One reason follows from limited comparability of diverse experiences gained in past jobs. As the experience set gets more diverse, it becomes more difficult to compare the different experiences. Then, drawing inferences from what was learned from these different experiences is harder. If an entrepreneur cannot understand the causal relationships between her experiences and specific outcomes, it is impossible for her to fully utilize the gained capabilities (Reed and Defillippi 1990), which lowers her entrepreneurial performance. With causal ambiguity, drawing correct inferences from what was the origin of the outcomes of the experiences of the entrepreneur is very difficult, if not impossible. Drawing wrong inferences, while believing these are right, comes with lower performance. Zollo (2009) shows that superstitious learning from rare strategic actions results in lower performance, arguing that, due to causal ambiguity, one draws wrong inferences while believing the opposite. Related to this, Åstebro and Yong (2016) find evidence that entrepreneurs who have experience in a wide variety of industries reveal lower entrepreneurial performance. They argue that having experience in a wide variety of industries comes at the cost of lower deep within-industry knowledge. The experiences within different industries are difficult to compare due to the idiosyncrasies of a specific industry, such as customer problems, new technologies, ways to serve the market, et cetera. Hence, this increases the likelihood of causal ambiguity due to the limited comparability across the diverse set of experiences.

Another factor causing experience diversity to have a negative effect on performance is associated with the entrepreneur's cognitive limitations. Individuals face neurophysiological limitations "to receive, store, retrieve, and process information without error" (Williamson 1975: 21). The cognitive capacity of an individual is exceeded when she receives more information than she is able to process. This can be understood as resulting from knowledge overload (Baron 1998; Gilbert et al. 1992). In case of knowledge overload, the entrepreneur simply cannot process all the information, hence being unable to exploit the learning opportunities offered by experience to the fullest.

A further argument involves minimization of cognitive effort, suggesting that individuals tend to minimize their cognitive effort in the same way as they have the tendency to minimize physical effort. Mental effort is minimized by using "short-cuts" in thinking (Baron 1998), which would enable the entrepreneur to process more information. Both limited cognitive capacity and cognitive effort minimization reduce the understanding of the causal relationships between the entrepreneur's experiences and the corresponding outcomes. This will result in an entrepreneur being unable to fully utilize the gained capabilities, thereby lowering her entrepreneurial performance.

The negative relationship between experience diversity and entrepreneurial performance amplifies if experience diversity increases. If entrepreneurs are not aware of the errors in their knowledge and skill base, stemming from causal ambiguity and limited cognitive capacity, then new experiences are made sense of through the lens of their erroneous knowledge and skill base. This will further enlarge causal ambiguity. Hence, what once used to be small errors may grow larger as the diversity of the knowledge and skill base increases. Combining the positive and negative relationship between experience diversity and performance, we expect that entrepreneurial performance will be low at both little and much experience diversity. This gives an inverted U-shaped relationship, implying that experiential diversity is associated with an inflection point at which entrepreneurial performance is maximal for medium levels of experience diversity.

Hypothesis 2 (H2): The relationship between experience diversity and this entrepreneur's performance is inverted U-shaped, such that entrepreneurs with low and high experience diversity are associated with lower performance than entrepreneurs with medium experience diversity.

3 Data and methods

3.1 The data

The data are obtained from the National Longitudinal Survey of Youth performed by the US Bureau of Labor Statistics over the period 1979–2010 (NLSY79). The data involve information from 24 rounds of interviews. Respondents were interviewed annually up to 1994 and bi-annually after 1994. The data relates to 9964 respondents aged between 14 and 22 years in 1979. Not all individuals replied to the survey in each round, making this dataset unbalanced. Moreover, not all respondents are or have been entrepreneurs. The number of individuals who are or have been entrepreneur is 1304. The total number of observations is 2120. The average number of year-observations per individual is 1.6, and the maximum number of year-observations per individual is 6.

The dependent variable is entrepreneurial performance. *Entrepreneurial performance* is measured as the gross annual income obtained from wage and business income, which is measured in US dollars. This measure of performance has been adopted following van Praag et al. (2012), working with the same dataset. As the distribution of this measure is positively skewed, *entrepreneurial performance* is expressed in logarithmic units. To not lose observations, we added 1 to the gross annual income as 260 observations had a gross annual income of zero.

The independent variables relate to the entrepreneur's experience. Regarding experiential type (H1), Minniti and Bygrave (2001) argue that entrepreneurs need two types of knowledge, namely knowledge from the industry and knowledge about being an entrepreneur. Therefore, following Minniti and Bygrave (2001), two measures of an entrepreneur's experience have been created. First, *entrepreneurial experience* is an estimate of an individual's total number of years of experience with being an entrepreneur. This includes both the experience as an entrepreneur before the last transition to entrepreneurship and the experience gained since the last transition to entrepreneurship. Second, *industry experience* indicates the total number of years the entrepreneur has worked in the same industry as the current industry before becoming an entrepreneur.

The learning literature agrees that experience depreciates over time: that is, experience gained recently is more important for success than experience gained longer ago (e.g., Arrazola and Hevia 2004; Arthur and Huntley 2005; Boone et al. 2008; Darr et al. 1995; Groot 1998; Madsen and Desai 2010). However, consensus is lacking regarding the depreciation rate of experience, with depreciation rates being reported that range from 67 to 96 % per month (Argote and Epple 1990; Argote et al. 1990; Benkard 2000; Epple et al. 1996) to 11–17 % per year (Groot 1998). For example, Madsen and Desai (2010) show that experience from success depreciates at a higher rate than experience from failure, with 66 and 11 % per year, respectively. As we do not know whether and when the self-employed in our sample encountered failures and successes, we ran estimates using a 10, a 20, and a 30 % depreciation rate for experience. Furthermore, we run the model without depreciating for experience, implying a 0 % rate.

Following Åstebro and Thompson (2011) and Lechmann and Schnabel (2014), experience diversity (H2) is measured using two proxies: the number of skills linked to an entrepreneur's past jobs (*skill experience diversity*), and the number of knowledge fields associated with the entrepreneur's past jobs (*knowledge experience diversity*). Although knowledge and skills are both gained from experience and, thus, are closely related, they are not the same (Nass 1994). Hence, we include them both in this study. Data are retrieved from the Occupational Information Network Database (O*NET). This is a Web site developed for the US Department of Labor, Employment and Training Administration. O*NET provides job-analytic data for 1122 occupations (SOC classified), such as required skills, knowledge fields, abilities, and tasks. Each skill and knowledge field is rated on a 1-to-5 scale according to importance. We searched for required skills and knowledge fields with a score equal or above 4. The NLSY79 data refer to 1970 SOC codes, whereas O*NET applies 2010 SOC codes. Therefore, the 2010 SOC codes were first converted to 1970 SOC codes before occupation matching.

Knowledge experience diversity is measured as the total number of unique knowledge fields associated with all past occupations and *skill experience diversity* as the total number of unique skills associated with all past occupations. Hence, when the skill "complex problem solving" occurs in two of the individual's past occupations, this is only counted as one skill. The experience of an entrepreneur is more diverse when the cumulative number of skills associated with her prior jobs is higher, or when the cumulative number of knowledge fields linked to her past jobs is higher. For both variables, as above, we ran estimates using a 10, a 20, and a 30 % depreciation rate for experience. In addition, we estimate the model without depreciating for experience.

Control variables are the *age* of an entrepreneur, the highest obtained degree of formal *education*, *marital status* (1 = "married"), *gender* (1 = "male"), *ethnicity* (dummies for "Hispanic" and "Black," where "non-Black, non-Hispanic" is the baseline), *limiting health* (which is 1 if the individual's health limits her in the kind of work she can do), and the average number of *hours worked per year*. These control variables are selected in line with Dahl and Sorenson (2012), Lazear (2005), Lechmann and Schnabel (2014), van der Sluis et al. (2008), and Hartog et al. (2010). Studies have found age to have a non-linear effect on performance (Dahl and Sorenson 2012; van der Sluis et al. 2008). Therefore, *age* and its quadratic terms are included. We measured *age* in years. *Education* is measured as the highest grade completed. This is an ordinal variable ranging from 1 to 20, where 1 is 1st grade and 20 is 8 or more years of college and university. Studies have established that the entrepreneur's education positively influences entrepreneurial performance (van der Sluis et al. 2008), that male entrepreneurs outperform their female counterparts (Dahl and Sorenson 2012), that entrepreneurs belonging to an ethnic minority reveal a lower entrepreneurial performance (van der Sluis et al. 2008), and that performance is lower if an entrepreneur's health limits her in the amount of work she can do (Hartog et al. 2010; van der Sluis et al. 2008). The average number of hours worked per year is included, as some entrepreneurs work twice as much as other entrepreneurs, which is logically linked to differences in entrepreneurial performance.

3.2 The model

To test the hypotheses, the model is estimated in three steps. First, a model is run with the control variables and *entrepreneurial experience* and *industry experience* (H1). Second, the model is estimated with experience diversity measured as *knowledge experience diversity* added, followed, third, by a model with experience diversity measured as *skill experience diversity* added (H2). *Knowledge experience diversity* and *skill experience diversity* are separately included in the model because of, empirically, the high correlation between the two types of experience diversity ($r = 0.95$, $p < .000$), as reported in Table 1. Furthermore, theoretically, the effect of knowledge experience diversity on performance is expected to be similar to that of skill experience diversity. The Hausman test indicates a preference for random effect specifications. Thus, to assess the relationship between experience diversity and entrepreneurial performance, generalized least squares random effects models are estimated.

4 Results

Table 1 presents the descriptive statistics. Approximately two-third of the entrepreneurs are male. On average, entrepreneurs cumulated 5.07 skills and 2.01 knowledge fields. The number of skills an entrepreneur possesses ranges from 0 to 45, whereas the number of knowledge fields varies from 0 to 26. None of the variables of interest are correlated above 0.70, except for the correlation between *skill experience diversity* and *knowledge experience diversity*, as discussed above. This is why these two measures of experience diversity are not included in the model at the same time.

Table 2 presents the estimates with *knowledge experience diversity* as the measure for experience diversity.

Table 1 Descriptive statistics and correlations

	Variable	Mean	Std.Dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.	ln(Income)	8.79	3.54	1.00								
2.	Gender *(male = 1)*	0.64	0.48	0.17	1.00							
3.	Age	43.46	9.02	0.09	−0.09	1.00						
4.	Limiting health *(yes = 1)*	0.08	0.27	−0.06	0.04	0.12	1.00					
5.	Marital status *(married = 1)*	0.57	0.50	0.08	−0.01	0.34	0.05	1.00				
6.	Education	13.77	2.63	0.12	0.08	0.17	−0.08	0.10	1.00			
7.	Ethnicity *(Hispanic = 1)*	0.16	0.37	0.06	−0.06	0.00	−0.01	−0.09	−0.21	1.00		
8.	Ethnicity *(Black = 1)*	0.22	0.42	0.07	−0.02	0.10	−0.05	−0.06	0.01	−0.16	1.00	
9.	Hours worked per year	2145.51	1038.16	0.37	0.17	0.26	0.02	0.19	0.03	−0.01	0.08	1.00
10.	Experience self-employed *(in years)*	2.83	1.36	0.01	0.04	0.44	0.05	0.19	−0.01	0.00	0.03	0.22
11.	Industry experience *(in years)*	0.46	1.02	0.26	0.11	0.39	0.01	0.23	0.13	−0.02	0.11	0.38
12.	Skills experience diversity	1.37	1.17	0.19	0.12	0.20	0.01	0.09	0.22	−0.18	−0.03	0.23
13.	Knowledge experience diversity	2.01	3.32	0.20	0.12	0.21	0.01	0.12	0.21	−0.15	−0.03	0.24
14.	Agriculture *(yes = 1)*	0.18	0.38	0.02	0.25	0.08	0.12	0.00	−0.09	−0.07	−0.07	0.18
15.	Mining *(yes = 1)*	0.01	0.08	−0.02	0.06	−0.06	−0.02	−0.02	0.01	−0.03	−0.03	−0.07
16.	Construction *(yes = 1)*	0.01	0.08	0.04	0.06	−0.04	−0.02	−0.02	0.03	−0.03	0.05	0.03
17.	Manufacturing *(yes = 1)*	0.05	0.22	0.09	0.02	−0.03	−0.06	0.03	0.02	−0.07	0.04	0.10
18.	Transportation *(yes = 1)*	0.03	0.16	−0.01	0.08	0.02	−0.04	0.01	−0.04	0.00	−0.03	0.08
19.	Trade *(yes = 1)*	0.02	0.14	0.03	0.00	0.02	0.02	0.04	−0.02	−0.06	−0.01	0.08
20.	Finance *(yes = 1)*	0.11	0.31	0.01	0.03	−0.12	−0.04	−0.03	−0.04	0.10	−0.02	0.04
21.	Services *(yes = 1)*	0.65	0.48	−0.01	−0.25	0.00	−0.05	0.06	0.14	0.00	0.09	−0.16
22.	Public administration *(yes = 1)*	0.02	0.14	0.09	0.12	0.04	−0.04	0.13	−0.05	−0.06	0.15	0.15
23.	Work experience	12.39	5.06	0.19	−0.07	0.74	0.03	0.32	0.14	−0.08	−0.03	0.32

	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.
1.														
2.														
3.														
4.														
5.														
6.														
7.														
8.														
9.														
10.	1.00													
11.	0.41	1.00												
12.	0.20	0.19	1.00											
13.	0.18	0.21	0.92	1.00										
14.	0.13	0.08	0.13	0.17	1.00									
15.	0.01	−0.06	0.00	0.02	−0.04	1.00								
16.	−0.02	−0.03	0.07	0.05	0.03	−0.01	1.00							
17.	−0.06	0.05	0.08	0.08	−0.06	−0.02	−0.02	1.00						
18.	0.05	0.10	0.03	0.06	−0.04	−0.01	−0.01	0.13	1.00					
19.	0.00	0.08	−0.01	−0.02	−0.03	−0.01	−0.01	0.03	−0.02	1.00				
20.	−0.09	0.05	−0.06	−0.02	−0.14	−0.03	−0.03	−0.02	−0.06	−0.05	1.00			
21.	−0.08	−0.04	−0.09	−0.17	−0.55	−0.11	−0.11	−0.26	−0.20	−0.11	−0.33	1.00		
22.	0.08	0.26	0.10	0.09	−0.03	−0.01	−0.01	−0.03	0.07	−0.02	0.00	−0.07	1.00	
23.	0.51	0.46	0.34	0.37	0.10	−0.04	−0.02	0.01	0.04	0.03	−0.06	−0.08	0.06	1.00

Column 1 shows the estimates for the baseline model including *entrepreneurial experience* and *industry experience* (H1), and columns 2, 3, 4, and 5 report the estimates for the model with a 30 %, depreciation rate, a 20 % depreciation rate, a 10 % depreciation rate, and without depreciating for experience, respectively. *Knowledge experience diversity* is used as a measure for experience diversity. Similarly, Table 3 reports the estimates with *skill experience diversity* as a measure for experience diversity.

Regarding H1, *entrepreneurial experience* and *industry experience* are insignificantly related to entrepreneurial performance. When including measures of experience diversity in the model in columns 2 and 3, the coefficients of *entrepreneurial experience* and *industry experience* do not switch signs, but continue to have an insignificant effect on entrepreneurial performance. *Entrepreneurial experience* and *industry experience* remain insignificantly associated with entrepreneurial performance if we change the rate for

Table 2 Knowledge experience diversity

	(1) lnincome Baseline	(2) lnincome 30 %	(3) lnincome 20 %	(4) lnincome 10 %	(5) lnincome No depreciation
Gender *(male = 1)*	0.177	0.169	0.173	0.180	0.188
	(0.164)	(0.165)	(0.165)	(0.165)	(0.166)
Age	−0.111	−0.116	−0.120	−0.126	−0.144
	(0.088)	(0.088)	(0.088)	(0.089)	(0.090)
Age^2	0.002	0.002	0.002	0.002	0.002 t
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Limiting health *(yes = 1)*	−0.495 t	−0.493 t	−0.500 t	−0.502 t	−0.478 t
	(0.278)	(0.279)	(0.279)	(0.278)	(0.278)
Marital status *(married = 1)*	0.561***	0.559***	0.561***	0.560***	0.563***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)
Education	0.179***	0.177***	0.177***	0.176***	0.178***
	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)
Ethnicity *(Hispanic = 1)*	0.436*	0.453*	0.445*	0.430 t	0.440*
	(0.220)	(0.220)	(0.220)	(0.221)	(0.221)
Ethnicity *(Black = 1)*	0.031	0.046	0.037	0.027	0.036
	(0.195)	(0.195)	(0.195)	(0.196)	(0.198)
Hours worked per year	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrepreneurial experience *(in years)*	−0.054	−0.064	−0.054	−0.040	−0.020
	(0.065)	(0.100)	(0.065)	(0.036)	(0.020)
Industry experience *(in years)*	0.155	0.136	0.125	0.106	0.076
	(0.104)	(0.138)	(0.109)	(0.080)	(0.052)
Knowledge experience diversity		0.019	−0.005	0.004	0.062
		(0.091)	(0.073)	(0.054)	(0.043)
Knowledge experience diversity^2		0.001	0.002	0.001	−0.003
		(0.005)	(0.004)	(0.003)	(0.002)
Constant	6.082***	6.102***	6.220***	6.349***	6.535***
	(1.578)	(1.592)	(1.586)	(1.589)	(1.603)
Observations	2120	2120	2120	2120	2120
R^2	0.071	0.072	0.072	0.072	0.072
Number of ID	1304	1304	1304	1304	1304

Standard errors in parentheses ***$p < 0.001$, ** $p < 0.01$, * $p < 0.05$, t $p < 0.10$

Table 3 Skill experience diversity[3]

	(1) lnincome Baseline	(2) lnincome 30 %	(3) lnincome 20 %	(4) lnincome 10 %	(5) lnincome No depreciation
Gender *(male = 1)*	0.177	0.169	0.176	0.183	0.208
	(0.165)	(0.165)	(0.165)	(0.166)	(0.166)
Age	−0.111	−0.115	−0.118	−0.123	−0.150 t
	(0.088)	(0.088)	(0.088)	(0.089)	(0.090)
Age^2	0.002	0.002	0.002	0.002	0.002 t
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Limiting health *(yes = 1)*	−0.495 t	−0.495 t	−0.501 t	−0.501 t	−0.471 t
	(0.278)	(0.279)	(0.279)	(0.279)	(0.277)
Marital status *(married = 1)*	0.561***	0.563***	0.564***	0.564***	0.574***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.160)
Education	0.179***	0.177***	0.178***	0.177***	0.177***
	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)
Ethnicity *(Hispanic = 1)*	0.436*	0.453*	0.444*	0.428 t	0.467*
	(0.220)	(0.220)	(0.220)	(0.221)	(0.221)
Ethnicity *(Black = 1)*	0.031	0.045	0.034	0.024	0.022
	(0.195)	(0.195)	(0.200)	(0.197)	(0.198)
Hours worked per year	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrepreneurial experience *(in years)*	−0.054	−0.066	−0.055	−0.040	−0.015
	(0.065)	(0.100)	(0.065)	(0.036)	(0.020)
Industry experience *(in years)*	0.155	0.143	0.129	0.109	0.077
	(0.104)	(0.138)	(0.108)	(0.080)	(0.052)
Skill experience diversity		−0.031	−0.110	−0.008	0.621*
		(0.422)	(0.335)	(0.255)	(0.024)
Skill experience diversity^2		0.053	0.066	0.017	−0.134**
		(0.120)	(0.096)	(0.077)	(0.050)
Constant	6.082***	6.108***	6.200***	6.299***	6.395***
	(1.579)	(1.591)	(1.583)	(1.587)	(1.601)
Observations	2120	2120	2120	2120	2120
R^2	0.071	0.071	0.072	0.071	0.074
Number of ID	1304	1304	1304	1304	1304

Standard errors in parentheses ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, t $p < 0.10$

[3] Skill experience diversity is divided by 10; otherwise, the effect would not be visible, given that we report in three decimals.

which we depreciate experience. Hence, H1 is not supported.

The data partially support the second hypothesis. As can be seen in Table 2, we fail to find a significant relationship between *knowledge experience diversity* and entrepreneurial performance. The coefficient of *knowledge experience diversity* remains insignificant when we change the rate applied to depreciate experience. In Table 3, we can see that experience diversity measured as *skill experience diversity* is insignificantly related to entrepreneurial performance, except if we do not depreciate for experience. If we do not apply a depreciation rate, we find an inverted U-shaped relationship between *skill experience diversity* and entrepreneurial performance. The Fieller method has been applied to check whether the optimum of the inverted U lies within the data range and to compute the confidence interval of the optimum following Haans et al. (2015).

The maximum of the inverted U is at 23.20 skills (t = 2.01, p = .023, 95 % CI [18.30, 43.70]). Hence, 23 skills is the optimal number: possessing less or more than 23 skills is associated with lower entrepreneurial performance. This is also reflected in Fig. 1, which gives the marginal effect plot of *skill experience diversity*.

Tables 4 and 5 present the estimates for the models in which we control for industry effects. We chose the industry categories following the SIC classification scheme (Occupational Safety and Health Administration n.d.). In Table 4, *knowledge experience diversity* is used as a measure for experience diversity. Table 5 presents the estimates with *skill experience diversity*. Column 1 provides the estimates of the model with a 30 % depreciation rate for experience, column 2 with a 20 % depreciation rate, column 3 with a 10 % depreciation rate, and column 4 with no depreciation for experience. If we control for industry effects, a very large number of the observations is lost, due to missing values: of the 1304 original observations, only 375 remain. Nevertheless, the fit of the model drastically improves: whereas the model without controlling for industry effects explains about 7.2 % of the variation in entrepreneurial performance, the model in which industry effects are controlled for explains about 25 % of the variation in entrepreneurial performance.

When controlling for industry effects, the coefficients *industry experience* and *entrepreneurial experience* turn significant. *Industry experience* is positively associated with entrepreneurial performance. However, *entrepreneurial experience* is negatively related to entrepreneurial performance. The coefficients of *industry experience* and *entrepreneurial experience* do not switch signs and continue to be significantly related to entrepreneurial performance when we change the measure of experience diversity or when we change the depreciation rates for experience. Therefore, when we control for industry effects, H1 is partially supported—i.e., *industry experience* is positively related to performance, but *entrepreneurial experience* is not.

The effects of *knowledge experience diversity* and *skill experience diversity* are robust. *Knowledge experience diversity* remains to have an insignificant effect on entrepreneurial performance when controlling for industry effects. We fail to find a significant relationship between *skill experience diversity* and entrepreneurial performance if we depreciate for experience, but we do find an inverted-U shaped relationship if we do not depreciate for experience. The Fieller method indicates that the maximum of the inverted U is at 23.97 skills (t = 2.01, p = .023, 95 % CI [18.30, 43.70]). Thus, 24 skills is the optimal number of skills to cumulate for an entrepreneur: possessing less or more than 24 skills is associated with lower entrepreneurial performance. Figure 2 shows the marginal effects of the inverted U relationship between *skill experience diversity* and entrepreneurial performance when controlling for industry effects.

4.1 Robustness checks

We performed several robustness checks. First, as we fail to find a non-linear relationship between experience diversity and entrepreneurial performance in most of our

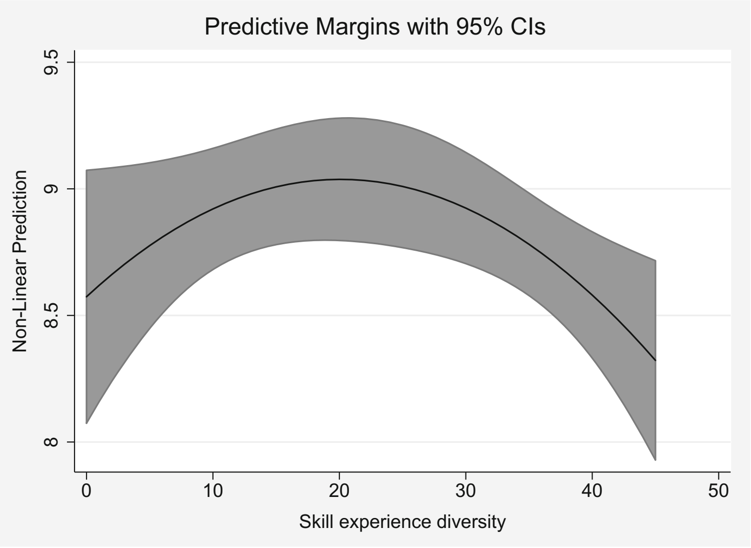

Fig. 1 Marginal effect of *skill experience diversity* without controlling for industry

Table 4 Knowledge experience diversity controlling for industry

	(1) lnincome 30 %	(2) lnincome 20 %	(3) lnincome 10 %	(4) lnincome No depreciation
Gender *(male = 1)*	0.498**	0.501**	0.510**	0.555**
	(0.189)	(0.189)	(0.190)	(0.190)
Age	0.703***	0.685***	0.658***	0.641***
	(0.158)	(0.158)	(0.159)	(0.159)
Age^2	−0.012***	−0.012***	−0.011***	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Limiting health *(yes = 1)*	−0.500	−0.498	−0.469	−0.397
	(0.359)	(0.359)	(0.360)	(0.359)
Marital status *(married = 1)*	−0.079	−0.088	−0.095	−0.110
	(0.191)	(0.191)	(0.191)	(0.191)
Education	0.015	0.019	0.026	0.032
	(0.043)	(0.043)	(0.043)	(0.042)
Ethnicity *(Hispanic = 1)*	0.744**	0.709**	0.665**	0.629*
	(0.255)	(0.256)	(0.258)	(0.258)
Ethnicity *(Black = 1)*	0.311	0.302	0.294	0.300
	(0.263)	(0.263)	(0.265)	(0.265)
Hours worked per year	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture *(yes = 1)*	−0.360	−0.311	−0.267	−0.232
	(0.365)	(0.363)	(0.361)	(0.359)
Mining *(yes = 1)*	0.206	0.219	0.280	0.381
	(1.143)	(1.145)	(1.147)	(1.143)
Construction *(yes = 1)*	0.603	0.683	0.773	0.809
	(1.122)	(1.124)	(1.126)	(1.125)
Manufacturing *(yes = 1)*	0.277	0.362	0.469	0.532
	(0.453)	(0.450)	(0.448)	(0.445)
Transportation *(yes = 1)*	−1.054 t	−1.012 t	−0.964 t	−0.898
	(0.587)	(0.586)	(0.585)	(0.582)
Trade *(yes = 1)*	−0.064	−0.027	0.025	0.066
	(0.640)	(0.640)	(0.639)	(0.635)
Finance *(yes = 1)*	−0.204	−0.169	−0.108	−0.020
	(0.377)	(0.375)	(0.373)	(0.369)
Services *(yes = 1)*	0.059	0.110	0.169	0.222
	(0.335)	(0.332)	(0.329)	(0.327)
Public administration *(yes = 1)*	−0.408	−0.327	−0.200	−0.092
	(0.674)	(0.670)	(0.665)	(0.658)
Entrepreneurial experience *(in years)*	−0.414**	−0.299**	−0.200**	−0.150***
	(0.144)	(0.103)	(0.070)	(0.044)
Industry experience *(in years)*	0.388***	0.313***	0.228***	0.144***
	(0.113)	(0.088)	(0.063)	(0.039)
Knowledge experience diversity	0.054	0.023	0.018	0.060
	(0.059)	(0.058)	(0.056)	(0.049)
Knowledge experience $diversity^2$	−0.000	0.001	0.001	−0.002

Table 4 (continued)

	(1) lnincome 30 %	(2) lnincome 20 %	(3) lnincome 10 %	(4) lnincome No depreciation
	(0.003)	(0.003)	(0.003)	(0.002)
Constant	−3.342	−3.172	−2.925	−2.891
	(2.235)	(2.242)	(2.254)	(2.252)
Observations	496	496	496	496
R^2	0.251	0.249	0.245	0.247
Number of ID	375	375	375	375

Standard errors in parentheses ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, t $p < 0.10$

models, we test for a linear relationship between experience diversity and entrepreneurial performance. In the models where industry effects are not controlled for, we do not find a significant linear relationship between our measures of experience diversity and entrepreneurial performance, as can be seen in Table 6. In contrast, if we control for industry effects, this relationship turns significant, as is shown in Table 7. *Knowledge experience diversity* is positively related to entrepreneurial performance if *knowledge experience diversity* is depreciated at a 10 % rate, 20 % rate, and 30 % rate. If we do not depreciate for experience, we fail to find a significant relationship between *knowledge experience diversity* and entrepreneurial performance. If experience is depreciated for, we have a positive linear relationship between *skill experience diversity* and entrepreneurial performance. This finding is consistent across depreciation rates of 10, 20, and 30 %.

Second, our results may be driven by a self-selection bias: i.e., individuals who have more diverse experiences are also the ones who are more likely to become an entrepreneur (Hsieh 2016; Lazear 2005; Lechmann and Schnabel 2014). Hence, a Heckman procedure is performed. An individual's risk attitude is used as an instrumental variable, as individuals who are risk loving are more likely to become entrepreneur than individuals who are risk averse (Blanchflower and Oswald 1998). Risk attitude is measured on a 10-point Likert scale, where 0 indicates "unwilling to take any risk" and 10 "fully prepared to take risk." Risk attitude is positively related to the likelihood to become an entrepreneur. Experience diversity is positively associated with the likelihood to become an entrepreneur if we do not depreciate for experience. If we do depreciate for experience, we do not find a significant relationship between experience diversity and the likelihood to become an entrepreneur. This is in line with Chen and Thompson's (2016) finding that the effect of experience diversity on the likelihood that an individual becomes an entrepreneur is dependent on the sample and regression specification used to test the relationship. The Inverse Mills Ratio is an insignificant predictor of entrepreneurial performance, indicating that our sample does not suffer from a self-selection bias.[1]

Third, we included working experience and its square in the model, since studies have found working experience to have a non-linear effect on performance (Dahl and Sorenson 2012; van der Sluis et al. 2008). Working experience is measured in years. We fail to find a significant relationship between work experience and entrepreneurial performance.[2]

5 Discussion and conclusion

This paper explores the relationship between entrepreneurial experience and entrepreneurial performance. As Lazear's jacks-of-all-trades theory argues, entrepreneurs need widespread experience across many different business areas to be able to perform all the tasks associated with being an entrepreneur (Lazear 2004, 2005). One of this theory's key arguments is that the more diverse an entrepreneur's experience, the more successful she will be. The evidence found by studies testing this argument is mixed. Hartog et al. (2010) find, just like Bublitz and Noseleit (2014), entrepreneurs to be more successful if their experiences are more diverse. Yet, Åstebro and

[1] Tables are available upon request.

[2] Tables are available upon request.

Table 5 Skill experience diversity controlling for industry[4]

	(1) lnincome 30 %	(2) lnincome 20 %	(3) lnincome 10 %	(4) lnincome No depreciation
Gender *(male = 1)*	0.485*	0.493**	0.508**	0.571**
	(0.189)	(0.189)	(0.189)	(0.189)
Age	0.703***	0.683***	0.652***	0.645***
	(0.158)	(0.158)	(0.159)	(0.158)
Age^2	−0.012***	−0.012***	−0.011***	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Limiting health *(yes = 1)*	−0.514	−0.505	−0.469	−0.387
	(0.359)	(0.359)	(0.360)	(0.358)
Marital status *(married = 1)*	−0.056	−0.066	−0.075	−0.089
	(0.191)	(0.191)	(0.192)	(0.190)
Education	0.016	0.020	0.027	0.034
	(0.043)	(0.043)	(0.043)	(0.043)
Ethnicity *(Hispanic = 1)*	0.755**	0.714**	0.675**	0.670**
	(0.257)	(0.258)	(0.260)	(0.259)
Ethnicity *(Black = 1)*	0.316	0.307	0.302	0.316
	(0.263)	(0.264)	(0.265)	(0.265)
Hours worked per year	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture *(yes = 1)*	−0.353	−0.315	−0.273	−0.217
	(0.363)	(0.362)	(0.361)	(0.357)
Mining *(yes = 1)*	0.193	0.214	0.314	0.510
	(1.145)	(1.147)	(1.149)	(1.139)
Construction *(yes = 1)*	0.495	0.574	0.689	0.739
	(1.125)	(1.125)	(1.128)	(1.121)
Manufacturing *(yes = 1)*	0.249	0.334	0.446	0.494
	(0.453)	(0.450)	(0.448)	(0.444)
Transportation *(yes = 1)*	−1.032 t	−0.999 t	−0.950	−0.908
	(0.586)	(0.585)	(0.584)	(0.579)
Trade *(yes = 1)*	−0.105	−0.053	−0.007	−0.038
	(0.640)	(0.639)	(0.639)	(0.633)
Finance *(yes = 1)*	−0.211	−0.174	−0.106	−0.014
	(0.377)	(0.375)	(0.373)	(0.367)
Services *(yes = 1)*	0.009	0.067	0.129	0.128
	(0.335)	(0.332)	(0.329)	(0.326)
Public administration *(yes = 1)*	−0.437	−0.365	−0.240	−0.127
	(0.675)	(0.670)	(0.666)	(0.655)
Entrepreneurial experience *(in years)*	−0.434**	−0.314**	−0.207**	−0.145**
	(0.144)	(0.104)	(0.070)	(0.045)
Industry experience *(in years)*	0.399***	0.321***	0.232***	0.145***
	(0.113)	(0.088)	(0.063)	(0.039)
Skill experience diversity	0.120	0.017	0.089	0.640**
	(0.283)	(0.276)	(0.270)	(0.248)
Skill experience diversity^2	0.032	0.053	0.018	−0.134*

Table 5 (continued)

	(1) lnincome 30 %	(2) lnincome 20 %	(3) lnincome 10 %	(4) lnincome No depreciation
	(0.078)	(0.074)	(0.069)	(0.057)
Constant	−3.301	−3.115	−2.865	−3.194
	(2.236)	(2.242)	(2.258)	(2.252)
Observations	496	496	496	496
R^2	0.251	0.249	0.244	0.253
Number of ID	375	375	375	375

Standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, t $p < 0.10$

[4] Skill experience diversity is divided by 10 (see footnote 3).

Thompson (2011) report the opposite. That is, the more diverse an entrepreneur's experience, the less successful she will be. The mixed effect found by Åstebro and Yong (2016) is in line with the contradicting findings of Åstebro and Thompson (2011) and Hartog et al. (2010). They reveal that experience diversity measured as the number of past occupations has a negative effect on performance, whereas experience diversity measured as the number of industries is shown to have a positive effect on performance.

We find experience diversity to be positively related to performance up to 23–24 skills: possessing more than 23–24 skills comes with lower entrepreneurial performance. This downside to experience diversity is only found in one case, namely when experience diversity is measured as the number of skills possessed and when we do not depreciate for experience. When depreciating for experience, the downside of experience diversity disappears, leaving experience diversity to be positively related to entrepreneurial performance. This finding indicates that old experience is negatively associated with entrepreneurial performance, whereas new experience is positively associated entrepreneurial performance. A possible explanation may be that older experience dilutes. So, an entrepreneur may have some idea of what she has learned in the past. However, as time passes, this comes less accurate and detailed, since experience deteriorates over time (Boone et al. 2008; Madsen and Desai 2010). The older experience, the more difficult it is for an entrepreneur to know the origin of the outcomes of her experiences. Hence, due to this lack of accurate and detailed knowledge, an entrepreneur may draw wrong inferences, while believing that she is drawing correct inferences. This may result in lower entrepreneurial

Fig. 2 Marginal effect of *Skill experience diversity* controlling for industry

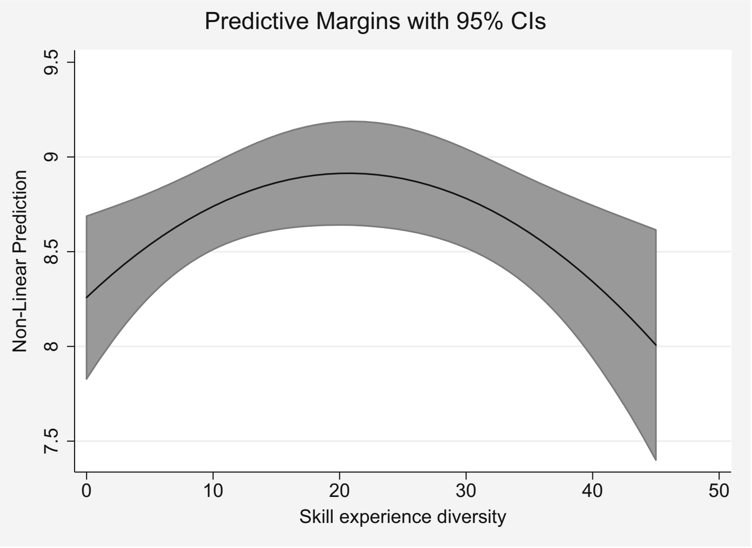

Table 6 Testing for a linear relationship not controlling for industry[5]

	(1) lnincome 30 %	(2) lnincome 30 %	(3) lnincome 20 %	(4) lnincome 20 %	(5) lnincome 10 %	(6) lnincome 10 %	(7) lnincome No depreciation	(8) lnincome No depreciation
Gender *(male = 1)*	0.168	0.168	0.172	0.171	0.182	0.179	0.188	0.185
	(0.164)	(0.164)	(0.165)	(0.165)	(0.165)	(0.165)	(0.166)	(0.166)
Age	−0.114	−0.115	−0.118	−0.119	−0.123	−0.125	−0.128	−0.131
	(0.088)	(0.088)	(0.088)	(0.088)	(0.089)	(0.089)	(0.090)	(0.090)
Age^2	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Limiting health *(yes = 1)*	−0.491 t	−0.491 t	−0.495 t	−0.495 t	−0.499 t	−0.499 t	−0.485 t	−0.483 t
	(0.278)	(0.278)	(0.278)	(0.278)	(0.278)	(0.278)	(0.278)	(0.278)
Marital status *(married = 1)*	0.562***	0.559***	0.561***	0.558***	0.562***	0.558***	0.562***	0.560***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)
Education	0.176***	0.176***	0.176***	0.176***	0.176***	0.175***	0.179***	0.178***
	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)
Ethnicity *(Hispanic = 1)*	0.455*	0.454*	0.445*	0.446*	0.427 t	0.429 t	0.420 t	0.421 t
	(0.220)	(0.220)	(0.220)	(0.220)	(0.221)	(0.220)	(0.221)	(0.221)
Ethnicity *(Black = 1)*	0.048	0.048	0.042	0.043	0.027	0.030	0.014	0.019
	(0.195)	(0.195)	(0.195)	(0.195)	(0.196)	(0.196)	(0.198)	(0.197)
Hours worked per year	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrepreneurial experience *(in years)*	−0.065	−0.063	−0.054	−0.053	−0.041	−0.041	−0.018	−0.019
	(0.100)	(0.100)	(0.065)	(0.065)	(0.036)	(0.036)	(0.020)	(0.020)
Industry experience *(in years)*	0.136	0.132	0.129	0.124	0.112	0.108	0.077	0.077
	(0.136)	(0.136)	(0.108)	(0.108)	(0.079)	(0.079)	(0.052)	(0.052)
Knowledge experience diversity		0.037		0.028		0.016		0.003
		(0.030)		(0.028)		(0.023)		(0.012)
Skill experience diversity	0.147		0.104		0.045		−0.002	
	(0.132)		(0.125)		(0.104)		(0.061)	
Constant	6.040***	6.069***	6.137***	6.165***	6.282***	6.325***	6.449***	6.508***
	(1.583)	(1.584)	(1.581)	(1.581)	(1.585)	(1.586)	(1.604)	(1.604)
Observations	2120	2120	2120	2120	2120	2120	2120	2120
R^2	0.071	0.071	0.071	0.071	0.071	0.072	0.071	0.071
Number of ID	1304	1304	1304	1304	1304	1304	1304	1304

Standard errors in parentheses ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, t $p < 0.10$

[5] Skill experience diversity is divided by 10 (see footnote 3).

performance (Reed and Defillippi 1990; Zollo 2009). Skills and knowledge learned from recent experiences are still accurate and have not deteriorated yet. Therefore, an entrepreneur is less likely to draw wrong inferences. Hence, excluding older experience from our measure of experience diversity causes the downside of experience to disappear, leaving a linear positive relationship between experience diversity and entrepreneurial performance.

Another of this study's contributions relates to our measure of experience diversity. Studies testing the jacks-of-all-trades theory use either skills currently possessed by entrepreneurs (Lechmann and Schnabel 2014), skills possessed before the start of their careers (Hartog et al. 2010), or the number of occupational fields and industries an entrepreneur has experience in (Åstebro and Thompson 2011; Åstebro and Yong 2016) to measure experience diversity. Our

Table 7 Testing for a linear relationship controlling for industry[6]

	(1) lnincome 30 %	(2) lnincome 30 %	(3) lnincome 20 %	(4) lnincome 20 %	(5) lnincome 10 %	(6) lnincome 10 %	(7) lnincome No depreciation	(8) lnincome No depreciation
Gender *(male = 1)*	0.482*	0.498**	0.492**	0.505**	0.509**	0.515**	0.538**	0.537**
	(0.189)	(0.188)	(0.189)	(0.189)	(0.189)	(0.189)	(0.189)	(0.189)
Age	0.699***	0.703***	0.677***	0.681***	0.650***	0.655***	0.645***	0.649***
	(0.158)	(0.158)	(0.158)	(0.158)	(0.158)	(0.158)	(0.159)	(0.158)
Age^2	−0.012***	−0.012***	−0.011***	−0.012***	−0.011***	−0.011***	−0.011***	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Limiting health *(yes = 1)*	−0.505	−0.500	−0.493	−0.490	−0.466	−0.464	−0.407	−0.401
	(0.358)	(0.358)	(0.358)	(0.358)	(0.359)	(0.359)	(0.360)	(0.359)
Marital status *(married = 1)*	−0.051	−0.079	−0.060	−0.085	−0.074	−0.094	−0.097	−0.112
	(0.191)	(0.190)	(0.191)	(0.191)	(0.192)	(0.191)	(0.191)	(0.191)
Education	0.016	0.015	0.019	0.018	0.027	0.025	0.037	0.033
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Ethnicity *(Hispanic = 1)*	0.765**	0.744**	0.734**	0.714**	0.682**	0.669**	0.616*	0.624*
	(0.255)	(0.255)	(0.257)	(0.256)	(0.258)	(0.257)	(0.259)	(0.258)
Ethnicity *(Black = 1)*	0.322	0.312	0.318	0.308	0.306	0.300	0.278	0.286
	(0.262)	(0.262)	(0.263)	(0.263)	(0.265)	(0.264)	(0.266)	(0.265)
Hours worked per year	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture *(yes = 1)*	−0.363	−0.360	−0.328	−0.326	−0.275	−0.275	−0.214	−0.220
	(0.362)	(0.362)	(0.361)	(0.361)	(0.360)	(0.360)	(0.359)	(0.358)
Mining *(yes = 1)*	0.240	0.206	0.293	0.256	0.339	0.304	0.395	0.365
	(1.139)	(1.139)	(1.140)	(1.141)	(1.144)	(1.144)	(1.143)	(1.142)
Construction *(yes = 1)*	0.488	0.603	0.572	0.675	0.689	0.767	0.804	0.843
	(1.123)	(1.121)	(1.125)	(1.122)	(1.127)	(1.125)	(1.125)	(1.123)
Manufacturing *(yes = 1)*	0.245	0.277	0.329	0.360	0.444	0.465	0.546	0.553
	(0.453)	(0.452)	(0.450)	(0.449)	(0.448)	(0.447)	(0.445)	(0.444)
Transportation *(yes = 1)*	−1.038 t	−1.054 t	−1.008 t	−1.026 t	−0.954	−0.973 t	−0.858	−0.880
	(0.586)	(0.585)	(0.584)	(0.584)	(0.584)	(0.584)	(0.581)	(0.581)
Trade *(yes = 1)*	−0.107	−0.064	−0.061	−0.019	−0.015	0.025	0.047	0.080
	(0.639)	(0.639)	(0.638)	(0.639)	(0.638)	(0.639)	(0.635)	(0.635)
Finance *(yes = 1)*	−0.207	−0.204	−0.164	−0.163	−0.102	−0.103	−0.030	−0.027
	(0.377)	(0.377)	(0.374)	(0.374)	(0.372)	(0.372)	(0.369)	(0.368)
Services *(yes = 1)*	−0.004	0.059	0.049	0.104	0.123	0.165	0.206	0.236
	(0.333)	(0.334)	(0.331)	(0.331)	(0.328)	(0.329)	(0.325)	(0.326)
Public administration *(yes = 1)*	−0.451	−0.408	−0.385	−0.344	−0.247	−0.215	−0.047	−0.038
	(0.673)	(0.672)	(0.669)	(0.668)	(0.665)	(0.663)	(0.657)	(0.655)
Entrepreneurial experience *(in years)*	−0.435**	−0.414**	−0.314**	−0.301**	−0.206**	−0.200**	−0.152***	−0.152***
	(0.144)	(0.143)	(0.103)	(0.103)	(0.070)	(0.070)	(0.045)	(0.045)
Industry experience *(in years)*	0.397***	0.387***	0.319***	0.311***	0.232***	0.227***	0.146***	0.145***
	(0.113)	(0.113)	(0.088)	(0.088)	(0.063)	(0.063)	(0.039)	(0.039)
Knowledge experience diversity		0.054**		0.047**		0.035*		0.023
		(0.018)		(0.018)		(0.017)		(0.015)
Skill experience diversity	0.232**		0.206**		0.155*		0.082	

Table 7 (continued)

	(1) lnincome 30 %	(2) lnincome 30 %	(3) lnincome 20 %	(4) lnincome 20 %	(5) lnincome 10 %	(6) lnincome 10 %	(7) lnincome No depreciation	(8) lnincome No depreciation
	(0.080)		(0.080)		(0.078)		(0.072)	
Constant	−3.283	−3.342	−3.096	−3.149	−2.873	−2.919	−2.924	−2.924
	(2.234)	(2.232)	(2.241)	(2.239)	(2.255)	(2.252)	(2.260)	(2.250)
Observations	496	496	496	496	496	496	496	496
R^2	0.251	0.251	0.248	0.249	0.244	0.244	0.244	0.246
Number of ID	375	375	375	375	375	375	375	375

Standard errors in parentheses *** $p < 0.001$, **$p < 0.01$, *$p < 0.05$, t $p < 0.10$

[6] Skill experience diversity is divided by 10 (see footnote 3)

study adds to this by creating time-varying measures in which we unpack the number of occupations into skill and knowledge sets gained in these occupations. Hence, our dataset allows us to construct a measure in which we cover both the skills gained in past occupations and the skills currently possessed by an entrepreneur. By doing so, we further open the black box of experience.

Although literature on learning considers knowledge and skills to be both outcomes of experience, discussion continues as to what the primary outcome of experience is. Some scholars take skills as the most important outcome of experience, an example being Levitt and March (1988). Others focus on knowledge as the most important outcome of experience. Nass (1994), for instance, finds knowledge to be the primary result of experience. We find *skill experience diversity* to have an inverted U-shaped relationship with performance if experience is not depreciated for, whereas we do not find such a relationship if experience diversity is measured as the number of knowledge domains. However, when depreciating for experience and controlling for industries, we reveal that the more diverse the knowledge of an entrepreneur, the higher her entrepreneurial performance. Similarly, the more skills an entrepreneur possesses, the higher her performance if we depreciate for experience and control for industries. Thus, although we find a relationship between experience diversity and performance for both measures of experience diversity, experience diversity measured in skills seems to be more robust across all our models, indicating that experience diversity measured in skills may be a better predictor for entrepreneurial performance than experience diversity measured in knowledge domains.

A possible explanation for this finding could be that skills possessed by an entrepreneur reflect her abilities, while knowledge consists of facts and procedures. Although the importance of knowledge of the market and market opportunities is evident, this is not enough if one does not possess the capabilities to implement this knowledge. Skills are therefore needed to deliver success, as skills reflect the capabilities of an entrepreneur needed to execute her activities. The essential importance of skills for an entrepreneur is also reflected in the very definition of an entrepreneur. Both the occupational and the behavioral notion of entrepreneurship define an entrepreneur on the basis of her skills (Shane and Venkataraman 2000; Sternberg and Wennekers 2005). The occupational notion of entrepreneurship considers someone to be an entrepreneur when this individual owns and manages a business, and the behavioral notion of entrepreneurship takes someone to be an entrepreneur when she identifies and exploits opportunities (Shane and Venkataraman 2000; Sternberg and Wennekers 2005). Hence, besides that skills are needed to produce success as skills reflect the capabilities of an entrepreneur, the critical importance of skills for an entrepreneur is also reflected in its very definition.

We find that entrepreneurial experience is negatively related to entrepreneurial performance, whereas industry experience is positively associated with entrepreneurial performance. A possible explanation for this twofold finding relates to what entrepreneurs learn. In the learning literature, several arguments have been put forward to explain potential downsides of experience and learning, such as limited comparability of past experiences, and hence causal ambiguity, as well as an individual's tendency to minimize cognitive effort

(Reed and Defillippi 1990; Zollo 2009), reducing the understanding of causal relationships associated with experiences. Therefore, an entrepreneur will not be able to exploit learning opportunities offered by any new experience to the fullest, as she does not fully understand the causal relationships between experiences and outcomes. Note that this finding contradicts with the standard human capital argument, as studies on human capital found both types of experience to have a small, yet positive effect on entrepreneurial success (Unger et al. 2011).

Another possible explanation for the found negative relationship between entrepreneurial experience and entrepreneurial performance is that entrepreneurs who have failure experience are treated differently than entrepreneurs who do not have failure experience by outside stakeholders. An entrepreneur's failure experience sends negative signals to an entrepreneur's environment. This may reduce the likelihood that she, for instance, will receive funding in the future (Gompers et al. 2010; Hsu 2007). Gompers et al. (2010) show that entrepreneurs with a track record of successes have an increased likelihood to receive the needed resources vis-à-vis entrepreneurs who have failed in the past.

This study has some limitations, one of which is the possible endogeneity of industry experience and entrepreneurial experience. Another of this study's limitations is that individuals could skip questions when answering the survey. They did not always indicate in which industry they were active or in which occupational field they had experience. Hence, the actual level of experience or the actual level of experience diversity may be higher than the reported level. The lack of complete industry experience data severely limits the size of the sample if we control for industry. Strikingly, we fail to find a relationship between the entrepreneur's experience (diversity) and entrepreneurial performance in most of our models estimated for the large sample of 1304 entrepreneurs, but do find experience and experience diversity to be significantly associated with performance in our much smaller sample of 375 entrepreneurs after controlling for industry. Hence, when the reported level of experience and experience diversity is more likely to accurately reflect the actual level, we do reveal that experience and experience diversity influence entrepreneurial performance.

Another of this study's limitations, associated with the NLSY79 and O*NET databases, is the absence of a perfect match between 1970 and 2010 SOC codes. The 2010 SOC codes are much more detailed. Thus, when information is aggregated to the 1970 SOC classification system, substantive detail is lost. For example, two 2010 SOC codes may be one 1970 SOC code. In this case, skill A may be important for profession A with 1970 SOC code B, but does not have to be important for profession C with 1970 SOC code B. The (unavoidable) aggregation implies the assumption that professions grouped under one 1970 SOC code are related. Therefore, within one 1970 SOC code, the level of importance may vary per profession to a certain degree, but not to the extent that a skill is very important for one profession and completely irrelevant for another within the same 1970 SOC code.

One more issue involves the question regarding the extent in which an entrepreneur's past successes and failures may moderate the relationship between experience diversity and entrepreneurial performance. If an entrepreneur has encountered many successes in her past career, the positive relation between experience diversity and entrepreneurial performance may decrease. These successes trigger lower - level learning (Appelbaum and Goransson 1997; Cope 2005). As they do not force an entrepreneur to rethink her routines, this makes it more difficult to draw correct inferences from what was experienced (Reed and Defillippi 1990). This, in turn, may increase causal ambiguity, resulting in an amplified negative relation between experience diversity and performance. The extent to which the relationship between experience diversity and performance depends on an entrepreneur's past successes and failures is an interesting topic for future research.

We examine the relationship between accumulated skill diversity and entrepreneurial performance, whereas Hartog et al. (2010) investigate the relationship between innate skill diversity and entrepreneurial performance. Hartog et al. (2010) find a positive association between innate skill diversity and entrepreneurial performance, and we provide evidence for a positive association with accumulated skill variety. A possible explanation for these similar entrepreneurial performance effects of innate and accumulated skill diversity may be that the two are highly correlated: individuals with high innate skill diversity might have many talents, driving them to select into a varied career path, hence accumulating more diverse experiences during their working career. However, how innate skill diversity relates to its accumulated counterpart has yet to be investigated. This reflects another interesting future research issue.

Compliance with ethical standards

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